IVLAB – Advanced Processing Image System

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Abstract

This paper describes the image processing tasks developed under a R&D project (iVLab project), between the Faculty of Engineering of Oporto University and an industrial machinery equipment leader in the production of equipments for the cork sector. The main objective of the project was to develop a system capable of classifying cork stoppers in different classes according to their surface characteristics; therefore, using grey scale image processing and pattern recognition techniques it was possible to develop a system able of learning each class characteristics and, afterwards, make its classification in different classes.

Keywords: image processing, pattern recognition, classification methods, characteristics extraction

1. Introduction

The challenging of value-added automation in industrial processes, due to the constant increase of competitiveness level and market demands, has a great strategic and economic impact for the companies from different economic sectors. In that context, there is an urgent need to modernize some of relevant traditional sectors. The cork industry is one of the sectors that are more and more seeking for automation of low added value activities. In fact, in this sector, cork inspection is one of least automated tasks due, mainly, to the complexity of inspection task, namely, the inspection of the natural cork material (lack of objectivity and uniform rules). In this paper, we present the approach followed for an automatic surface inspection system of cork stoppers in real industrial environment. The major requirement was to design and develop a system capable of classifying a cork stopper in different possible classes, through a reliable and repetitive characteristics extraction method, according to their surface characteristics, as well as taking into account a previous learning process of features corresponding to relevant visual features of each class.

The project was developed using several digital inspection cameras and a specific architecture designed for industrial environment. The results achieved so far, allow us to conclude that the system is able to inspect all surface with a speed of 4 cork stoppers per second. In this paper we present mainly the aspects related to the image processing activities considered in the project.

2. Image processing

2.1 Pre-processing

The pre-processing is usually the first step to be done in an image processing system, allowing the minimization of noise that appears during the image acquisition and also treats the images so they can be used for the following data processing.

The techniques used consisted in transforming a coloured image into grey scale, detecting the cork stopper boundaries and applying filters to improve the image quality.

2.1.1 Object detection

In order to minimize the processing time, the analysed area was restricted to the one that has the cork stopper. As there are differences between the top and the body images, different methodologies have to be applied to each one.

Tops

Initially the experiments were conducted in laboratory, where the working conditions are well defined and easily controllable so the cork stopper and the background were very distinct and it was possible to define an intensity value (threshold) that allowed differentiating pixels that belong to the cork stopper of the ones that don't.

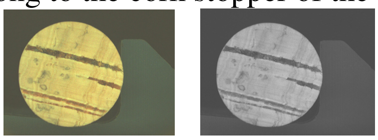


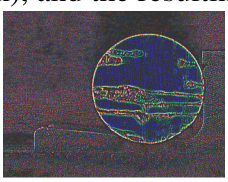
Fig. 1 – Top images of the cork before and after the grey scale switch

The threshold value that best characterizes the difference between the cork stopper and the background was experimentally determined and corresponds to the value to which we can obtain 85% of the total histogram's area. This is a dynamic threshold therefore it will react to external perturbations.
Once the threshold value is obtained, the image can be scanned for transitions and with all the points that correspond to transitions it is possible to use the min square method in order to get an estimate of the radius and the centre of the cork. The equations used are:

$$(x - x_o)^2 + (y - y_o)^2 = r^2 \qquad (1)$$

$$Y = \theta^T \times X \text{ and } \theta = \left(X^T \times X\right)^{-1} \times X^T \times Y \qquad (2)$$

This method showed very good results in laboratory, but when tested in a real situation detected transitions where they weren't, making the cork stopper detection incorrect.
Therefore it was tested a more robust solution using a more sophisticated method with known good results, the Hough transform.
For the edge detection is used the diagonal extended Laplacian filter multiplied by 2, which is based on the derivative notion and was refined with an image software.
This filter is applied, separately, to each of the three components that characterize a pixel (red, blue and green), and the resulting image is converted into grey scale.



-2	-2	-2
-2	16	-2
-2	-2	-2

Fig. 2 – Application of the edge detection filter to the image (left) and filter (right)

As you can see the cork stopper periphery is well defined and has pixels with intensity near the white colour so, using the circumference equation, it is possible to apply the Hough transform and calculate the centre and radius of the cork stopper.
This approach has shown good results, but the execution time of the Hough transform is too high becoming unacceptable in a real time application.
Having in mind the first results, the final approach consisted in applying to the grey scale image the Otsu method to find a threshold level, followed by the search of edges.
Finally, it was calculated an estimate of the cork centre using the average of all edge points, then the least probable points of belonging to the cork stopper edge were

eliminated (considering the distance of each point to the estimate centre and the standard radius) and the centre and radius calculated with the remaining points by the least square method. The next picture exemplifies the detection of the cork stopper edge with and without the elimination of the least probable points (the particle on the bottom right corner introduces noise).

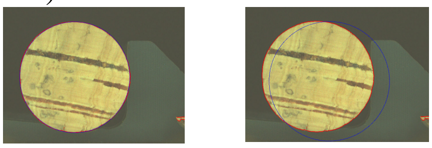


Fig. 3 – Edge detection with elimination of the least probable points (left) and without it (right)

This last method doesn't eliminate completely the incorrect detection of the cork's edge, however in order to minimize this error the following processing is only done to a region of interest that encloses 95% of the cork.

Body

The body parameters can be easily found, being only necessary to find the horizontal position of the cork, once the vertical is known. Thus, initially it is determined the threshold by the Otsu method and then the image is horizontally scanned for edges. The parameters are calculated as an average of the detected coordinates.

2.1.2 Filter Aplication

The application of filters allows not only minimizing the noise as well as attenuating or eliminating small irrelevant defects that exist in the surface of the cork. The applied filters use a window of 3X3 and take into account the eight neighbours of a pixel.

Average and Median Filters

The used average filter is based on the arithmetic mean, which attributes to the central pixel the average of all pixels in the window, this filter retains the low frequencies and eliminates the high ones, meaning a loss in detail.

$I(x,y)=\frac{1}{9}\sum_{j=-1}^{1}\sum_{i=-1}^{1} I(x+i,y+i)$, where I(x,y) represents the pixel intensity. (3)

The medium filter consists of attributing to the central pixel the medium of all pixels that belong to the window. This filter usually presents better results than the previous one, because it eliminates "salt and pepper" noise and keeps the objects limits.
Tests with the two filters demonstrate that the medium filter is better: the image is not so blurred and the defects contour is better defined, as can be seen in the next images:

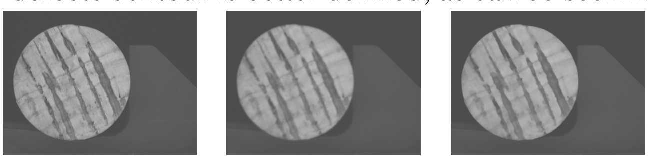


Fig. 4 – Original grey scale image (left), after average filter (centre), after median filter (right)

Binary dilatation and erosion filters

Dilatation and erosion are the basis for morphologic processing and can be applied to a binary image (with only two levels of intensity), or to a grey scale image.

These filters assume the existence of two distinct sets in Z^2: one that corresponds to the object of study (set A) and another (set B) that constitutes the structuring element. For the structuring element it was used a square of 2 pixels side.
Binary dilatation of A by B corresponds to the set of all displacements of B that overlap A by at least one pixel. In this case, and given the structure element, dilatation consists in classifying a good pixel as defective whenever it is the neighbour of a defective pixel.
Erosion corresponds to all pixels of A when B is totally contained in A, that is, it consists in tracing all pixels of A (which are defective ones) and classifying them as good if they are adjacent to a good pixel.
Combining these two types of morphologic operations gives origin to the opening (erosion followed by dilatation) or to the closing (dilatation followed by erosion).
Opening smoothes contours, eliminates lumps and isthmuses; closing also smoothes contours, but it tends to eliminate reentrances and small cracks.
Tests of repeatability demonstrated that the opening is more efficient, because there is a great variability in the small lumps that exist in the defects periphery, that affect in a strong way the area of the biggest defect.

Grey scale dilatation and erosion filters

Grey scale filters are different from their binary similar and in literature several definitions are given. In this in case it was used the extreme method because, in computational terms, it is the one that demands the least execution time.
So the erosion filter consists in scanning the image and attributing to the window central pixel the smallest intensity value and dilatation consists on attributing the highest value.
Therefore, erosion tends to minimize the clearest details and dilatation diminishes the darkest. These filters can be combined originating the opening and closing operations.
In order to minimize noise the opening and closing operations were used three consecutive times (in this order), allowing to eliminate or attenuate "salt and pepper" noise, as the medium filter does. The following images exemplify:

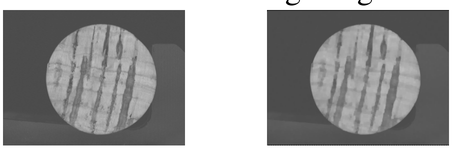


Fig. 5 – Original grey scale image (left) and after opening and closing grey scale filters (right)

This last method raised some difficulties in the process of cork characterization regarding good classes, because, generally, defects are small and with lighter colours.
It was also seen that corks from good classes tend to have small fine defects that, with the grey scale filters, are completely eliminated, losing precision in its detention.
After making some tests with the medium filter it was verified that the detection of this type of defects persists, so the final approach resulted in a mix of these two techniques in this sequence: grey scale opening filter - medium filter - grey scale opening filter.
This way it is possible to combine two important features: eliminate several types of noise (especially due to the opening filter) and preserving the defect structure (guaranteed by the medium filter). The following images illustrate this:

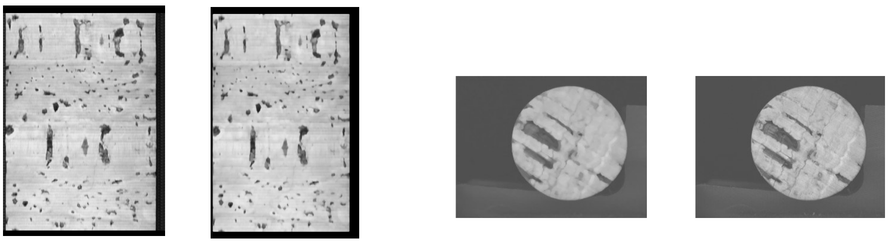


Fig. 6 – Original grey scale image (left) and image after using opening and median filters (right)

2.2 Image processing

Once the image is pre-processed, it is possible to determine which pixels are defects and extract the intended characteristics.

2.2.1 Defect pixels acknowledge

At this point the image is in grey scale and the defects appear with a darker intensity related to the good part of the cork, what propitiates the use of a threshold. Therefore, using the Otsu method and considering only the pixels that belong to the cork, it is possible to determine a threshold value that allows the differentiation of the defects.
The next picture presents a cork's histogram and the associated threshold value.

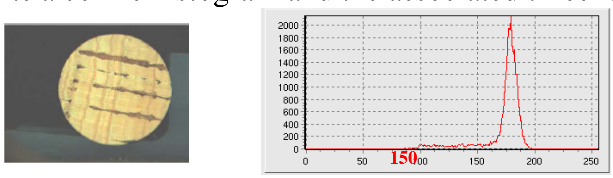


Fig. 7 – Original cork image (left) and the respective histogram with the threshold value (right)

Later, the region that contains the cork is scanned and pixels that have a value smaller than the threshold are labelled as defective and the ones that have higher as good, thus obtaining a binary image of the cork's surface.
This method showed good results for corks of weaker classes; however it presents limitations for corks whose defects are lighter. The following images present the histograms for each type of corks.

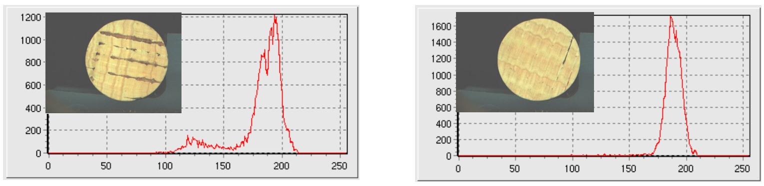


Fig. 8 – Histograms for corks with distinct characteristics

For good corks the threshold value obtained by the Otsu method is very high which implies that portions of cork that are not defects are classified as such. So it is necessary to apply another method to determine the threshold value if the defects are not sufficiently distinct from the cork.
Two threshold values are determined and the smaller is used for the defect detection. The first value is obtained by the Otsu method ($Thres_1$). For the second one ($Thres_2$) it is necessary to determine the intensity value ($I_{máx}$) where the histogram has its maximum and the delta intensity (ΔI) around the maximum that contains 98% of the total histogram.
If the achieved delta value is higher than 38 levels of intensity around the maximum then $Thres_2=255$ else $Thres_2=I_{max}-\Delta I$.
This second threshold will only affect good corks, which have the histogram more concentrated around the maximum, what implies that the value of 98% is reached before the 38 levels are covered. Corks that present a more dispersed histogram (corks with more defects) are not influenced by this threshold and the value will be the one obtained by the Otsu method.
If the final threshold value is still higher than 160 for the tops or 170 for the body the threshold is truncated in these values, respectively.

2.2.2 Defect grouping

At this point we only have the knowledge of the pixels that are defects and the ones that aren't, it is still necessary to establish a relation between the several pixels, grouping them as being part of one same defect. For such, the portion of the cork already binarized is horizontally scanned and whenever a defective pixel is detected, its neighbours are searched in order to verify if they are also defects. After grouping the pixels we can proceed to the characteristics extraction.

2.3 Characteristics extraction

The choice of the characteristics to be extracted is very important and has no consensus among specialists. It is also known that there are not rigid boundaries between classes and depending on the used characteristics, the classification can vary drastically.
The characteristics taken into consideration in this classification are: total area of defects, area of darker defects, total area of the edges defects, area of the biggest defect, average area of defects, maximum average/perimeter of the defects, width/length of the biggest crack and number of cracks.
Most of these characteristics can be extracted using known image processing techniques and mathematical relations therefore it is only detailed the width/length of the cracks because of its complexity.
Thus, for each crack, it is necessary to do a coordinate change for the small inertia axe coordinate system. In this coordinates system it is possible to make an estimate of the length using the length of the rectangle that surrounds the crack, and the width is approached by the average width of the crack in the new system.

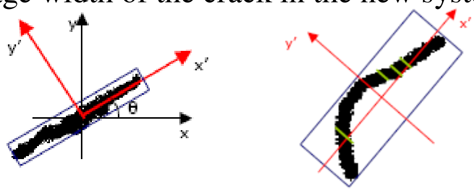


Fig. 9 – Coordinates change (left) and average width of the cracks (right)

3. Learning and classification

To make the parameterization process robust and repetitive, it is necessary to develop a system capable of learning each class characteristics by visual inspection of a sample.
Given the ambiguity that the corks classification implies the mechanism developed has its bases on fuzzy logic, once this area deals with problems where no absolute truths exist but degrees of belonging.
For the membership functions was chosen the Gaussian function because it characterizes most of the nature phenomenon and can be defined by only two parameters (average and standard deviation). Thus, for each class and parameter it is only necessary to calculate the averages using the expression:

$$\bar{x} = \frac{1}{N_{samples}} \sum_{i=1}^{N_{samples}} x_i \quad (4)$$

Having an estimate of the average, there are only used for the final average and standard deviation the ***x*** samples (user defined value) that are nearer to the first estimate, allowing the elimination of maverick values. The learning process is complete, and each class and characteristic is defined by a membership function.
In the classification process the cork images are acquired and its parameter values are obtained, afterwards it is determined the degree of membership of each parameter to each class.

Finally, for each class it is made the addition of the membership degrees of all parameters and the class that has the highest value will correspond to the attributed one. This operation is carried out separately in the three faces of the cork obtaining the individual classification for each top and body. The final choice of the cork's class can be defined in a controlled way and there are two possible types of classification.
In the first type the following premises are available:

$$\textit{Classification by the} \begin{pmatrix} \textit{best} \\ \textit{worst} \\ \textit{weight} \end{pmatrix} \textit{between the body and the} \begin{pmatrix} \textit{best} \\ \textit{worst} \\ \textit{average} \end{pmatrix} \textit{of the tops} \qquad (5)$$

That is, first the tops are evaluated and, depending on the choice, it is used the worse, best or average between them, after that it is made the evaluation of the result of the body and the result of the tops, being also able to choose the best, worse or weigh between them (example: 70% body, 30% tops).
In the second type of classification any type of combinations between the tops and the body can be made.
Besides the above types of classification it was also developed a method that allows improve/degrade a class by adjusting each parameter of the membership function.

Results

In order to evaluate the robustness of the characteristics extraction algorithm, as well as of the applied pre-processing methods, corks were submitted to a repetitive process of characteristics extraction, and afterwards it was made a statistical analysis of the results. These tests were done to the tops and to the body because the conditions of acquisition and illumination, among others, are different.
The analysis of the results showed that the body characteristics extraction presents good repeatability indices, in the order of 90%. It was also verified that the number of cracks and the area of the biggest defect are the characteristics that present less repeatability. The first one because the cracks detection seats in rigid parameters, so a small variation in one of these parameters implies the classification or not as a crack, the second is related to the fact that there are defects that are too near of each other and sometimes are joined by pre-processing filters and sometimes aren't.

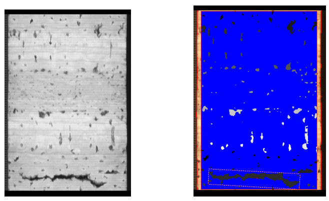


Fig. 10 – Body image processing result

It is also to have in mind that pixels which have intensity values near the threshold are a great source of error, because in one given acquisition, its proximity to the threshold value may lead the algorithm to classify them as defects or not in a non repetitive way.
For the tops two different tests were conducted, initially with the cork stopped and later with the cork in movement, that is, in its normal functioning conditions.
The following images show the result for one given cork:

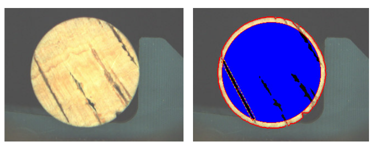


Fig. 11 – Top image processing result

The results analysis shows that the repeatability decreases significantly when the tests are done with the cork in movement. In fact, when the image is captured with the cork

stopped the results are pretty good, with repeatability around 99%, but when the images are captured with the cork in movement the repeatability drops below 90%.
The reason for this is intimately related with the way the illumination acts on the cork surface, because the object of study moves in a mechanical system that doesn't always place the cork in front of the camera in the same way.
For testing the learning process three classes of corks were used: Class A, Class B and Class C, ordered from the best to the worst (each class consists in 480 samples) and for different percentage of samples (remember that it is possible to consider the x best samples) the membership functions parameters were calculated.
As the classification stage is still in a development phase, the conducted tests still have produced few results and are based on the sample used for learning.
The analysis of the membership functions showed that there is a certain overlapping between them and the tests demonstrated that the classification using only the body or only the tops gives distinct results: the classification for the body tends to favour the best classes, on the contrary the classification for tops benefits the worse ones.
The manual rectification of the learning algorithm, which allows shaping the Gaussians in order to diminish the overlapping between the classes, demonstrated an improvement in the results and we could achieve a correlation around 60%.
It is of notice that the used samples, for each class, present little differentiation so it is possible that some corks of the sample were initially wrongly classified.

4. Conclusions

This paper describes the image processing system of iVlab project. The main objective was the design and development of an automatic inspection system capable of classifying and sorting cork stoppers at higher rate (real-time environment).
The pre-processing and pattern recognition techniques used for the corks classification are enunciated. Regarding the results it can be said that it was obtained a sufficiently satisfactory repeatability for the body parameters, however this repeatability came diminished for the tops.
It could also be seen that the illumination constitutes a critical point and the characteristics choice for the classification presents complex implications, so this choice must be subject to a careful analysis.
As for the classification algorithm the usage of a fuzzy logic based algorithm showed relatively promising results, leaving space for improvement to make it more robust and the possibility of a systematic use in industry.
As future improvements it could be interesting to include more characteristics, make use of colour image processing and make a more detailed evaluation of the algorithm potential.

5. Bibliography

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